

**Myocardium and papillary muscle derived radiomic features for left ventricular hypertrophy detection and hypertrophic cardiomyopathy versus hypertensive heart disease classification**

**Supplementary Materials**

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## **Supplementary methods**

### **Image processing**

Image processing and feature extraction were performed with Pyradiomics library (version 3.0.1) in a Python environment (version 3.7.10) in compliance with the latest image biomarker standardisation initiative (IBSI) documentation [1,2].

In this study, image processing included following steps: 1) resampling: images were resampled to  $1.0 \times 1.0 \times 1.0$  mm using appropriate interpolation method (B-spline interpolation for images and nearest neighbor for masks); 2) grey level normalization and discretization: VOIs were normalized and discretized to a fixed bin width of 16.

## **Supplementary figures**

### **Supplementary figure S1. An example of apical basal muscle bundle.**

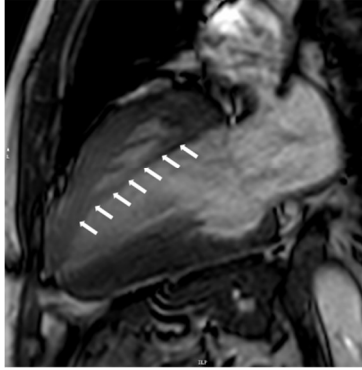
An example of apical-basal muscle bundle that is hard to distinguish from papillary muscle at short-axis cine images in a 59 years old male HCM patient. **(a)** Long axis 2 chamber view at end-diastole of this patient, apical-basal muscle bundle was denoted with white arrow. **(b)** short axis view at the end diastole, from top left (basal) to down right (apical), the apical-basal muscle bundle was denoted with a white triangle, in the short axis view, this muscle bundle is easily confused with papillary muscle.

### **Supplementary figure S2. Comparison of models using calibration curves.**

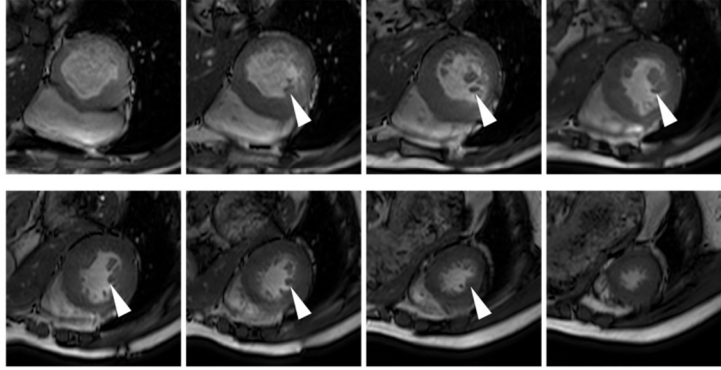
Calibration curves for different models were plotted, (a) showed calibration curves for detection task with MYO group; (b) showed calibration curves for differentiation task with MYO+PM group.

## Supplementary Figure S1.

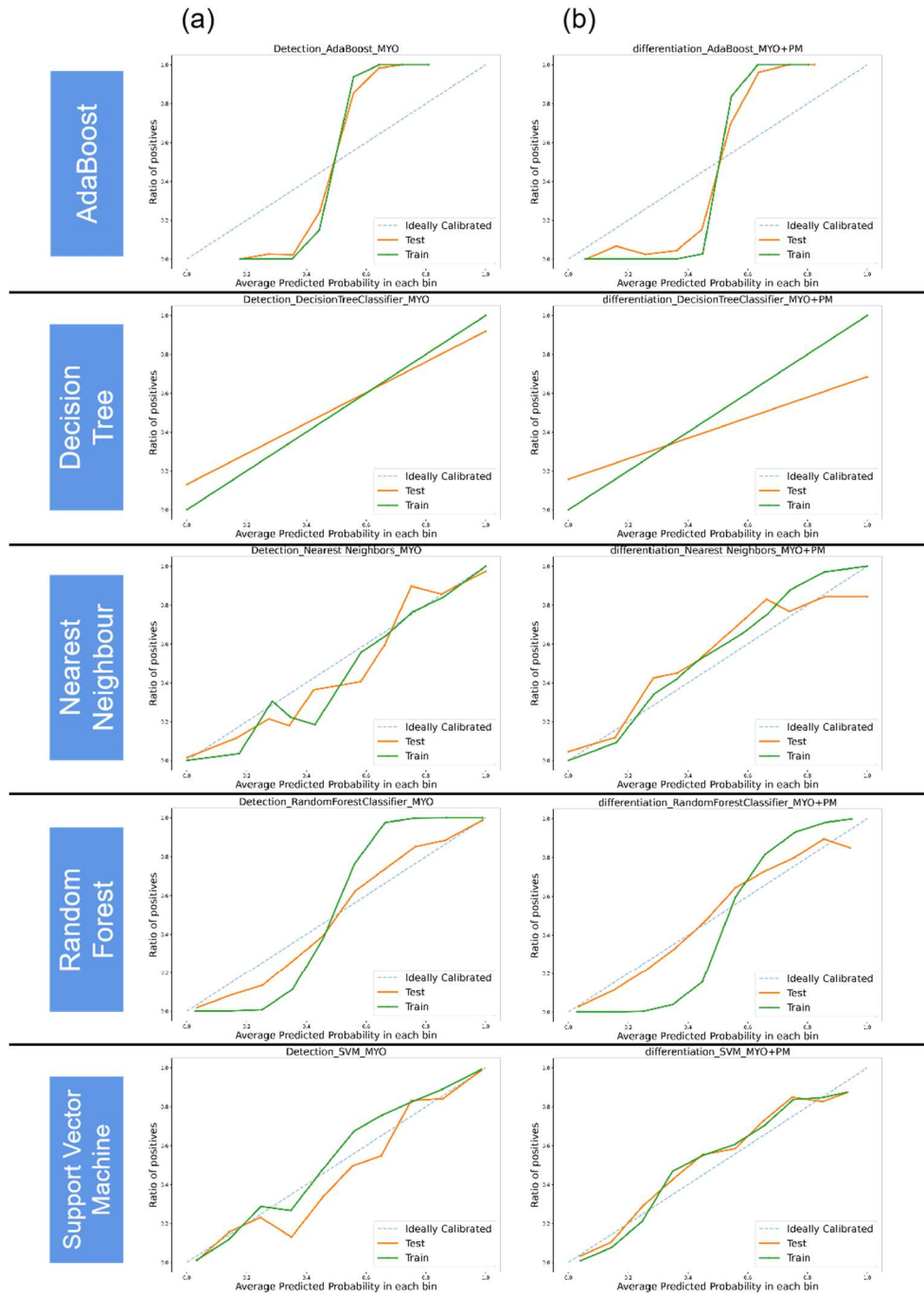
(a) Long axis 2 chamber at end diastole



(b) Short axis at end diastole from base to apex



Supplementary Figure S2.



**Supplementary Table S1.** Full list of extracted features.

VOI	Filter	Type		Number	Total
MYO	Original	Shape		14	1316
	Original: 1 LOG: 4 Wavelet: 8 Gradient: 1 Total: 14	Firstorder		18×14 (Total Filters)	
		Texture	NGTDM	5×14 (Total Filters)	
			GLCM	24×14 (Total Filters)	
			GLDM	14×14 (Total Filters)	
			GLRLM	16×14 (Total Filters)	
			GLSZM	16×14 (Total Filters)	
PM	Original	Shape		14	1316
	Original: 1 LOG: 4 Wavelet: 8 Gradient: 1 Total: 14	Firstorder		18×14 (Total Filters)	
		Texture	NGTDM	5×14 (Total Filters)	
			GLCM	24×14 (Total Filters)	
			GLDM	14×14 (Total Filters)	
			GLRLM	16×14 (Total Filters)	
			GLSZM	16×14 (Total Filters)	

GLCM: gray level co-occurrence matrix; GLDM: gray level dependence matrix; GLRLM : gray level run length matrix; GLSZM: gray level size zone matrix; LOG: Laplace of Gaussian; NGTDM: Neighboring gray tone difference matrix.

**Supplementary Table S2.** Full list of features ranked using Boruta method for detection task.

	MYO (N = 28)	Importan ce <sup>#</sup>	PM (N = 32)	Importan ce <sup>#</sup>
1	wavelet-LHL_glcml_Correlation	54.9	original_shape_Maximum2DDiameterRow	1.1
2	original_shape_Sphericity	11.0	wavelet-HLH_glcml_MCC	0.9
3	wavelet-HHH_firstorder_Median	9.8	wavelet-HHH_firstorder_Uniformity	0.8
4	wavelet-LHH_firstorder_Energy	4.4	wavelet-HHH_glcml_SumEntropy	0.4
5	wavelet-LHH_firstorder_Kurtosis	1.9	wavelet-LHH_glcml_ClusterShade	0.4
6	log-sigma-2-0-mm-3D_glcml_ClusterShade	1.5	wavelet-LLH_ngtdm_Contrast	0.3
7	wavelet-LLH_glrml_RunEntropy	1.3	wavelet-HLL_glcml_Correlation	0.3
8	wavelet-LHL_glcml_Imc2	0.8	original_shape_Flatness	0.3
9	wavelet-HLL_glcml_InverseVariance	0.6	wavelet-LHL_glcml_Imc1	0.2
1 0	wavelet-HLL_firstorder_Maximum	0.4	wavelet-LHH_ngtdm_Strength	0.2
1	wavelet-HHL_ngtdm_Contrast	0.3	wavelet-HLH_firstorder_Uniformity	0.1

1				
1				
2	log-sigma-2-0-mm-3D_glcm_Correlation	0.3	gradient_firstorder_Minimum	0.1
1				
3	gradient_glcm_Correlation	0.2	wavelet-LHL_firstorder_Kurtosis	0.1
1				
4	wavelet-HLL_glcm_Correlation	0.2	wavelet-HHH_glszm_GrayLevelNonUniformityNormal alized	0.1
1				
5	wavelet-LLH_ngtdm_Strength	0.2	original_shape_Elongation	0.1
1				
6	wavelet-LHH_glcm_ClusterShade	0.2	wavelet-HHL_firstorder_Kurtosis	0.1
1				
7	wavelet-LLH_glcm_Contrast	0.2	wavelet-HHH_glszm_GrayLevelNonUniformity	0.1
1	log-sigma-2-0-mm-3D_gldm_LargeDependenceHighGray LevelEmphasis	0.2	wavelet-HLH_firstorder_Kurtosis	0.1
8				
1	original_shape_Flatness	0.2	wavelet-HHL_gldm_DependenceNonUniformityN	<0.1



9				ormalized	
2					
0		wavelet-LHH_glszm_GrayLevelNonUniformity	<0.1	wavelet-HLH_firstorder_Mean	<0.1
2					
1		wavelet-HHL_glcm_MCC	<0.1	wavelet-HHL_ngtdm_Contrast	<0.1
2					
2		wavelet-LLH_firstorder_Mean	<0.1	wavelet-LHL_glszm_ZoneEntropy	<0.1
2					
3		wavelet-HHL_glcm_InverseVariance	<0.1	wavelet-HHL_glcm_ClusterShade	<0.1
2					
4		wavelet-LHL_glcm_ClusterShade	<0.1	wavelet-LLH_glszm_LargeAreaLowGrayLevelEmphasis	<0.1
2					
5		wavelet-HLH_firstorder_Minimum	<0.1	wavelet-LHL_gldm_SmallDependenceLowGrayLevelEmphasis	<0.1
2					
6		wavelet-HLL_glcm_Imc2	<0.1	wavelet-LHH_gldm_DependenceNonUniformityNormalized	<0.1
2					
		original_firstorder_Maximum	<0.1	wavelet-LLH_glcm_Correlation	<0.1

7				
2	wavelet-HHH_ngtdm_Strength	<0.1	wavelet-HHH_glszm_SizeZoneNonUniformityNor	<0.1
8			malized	
2			wavelet-HHL_glcml_Correlation	<0.1
9				
3			wavelet-LHL_firstorder_Skewness	<0.1
0				
3			wavelet-HHH_firstorder_Maximum	<0.1
1				
3			wavelet-LLH_glcml_Idmn	<0.1
2				

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# The maximal shadow feature importance is 0.2.

GLCM: gray level co-occurrence matrix; GLDM: gray level dependence matrix; GLRLM : gray level run length matrix; GLSZM: gray level size zone matrix; LOG: Laplace of Gaussian; NGTDM: Neighboring gray tone difference matrix.

Other abbreviation for specific features could be found in Pyradiomics documentation.

**Supplementary Table S3.** Full list of features ranked using Boruta method for differentiation task.

	MYO (N = 8)	Importance <sup>#</sup>	PM (N = 12)	Importance <sup>#</sup>
1	gradient_glcml_Correlation	37.5	original_shape_Maximum2DDiameterSlice	10.4
2	original_shape_Sphericity	4.9	log-sigma-5-0-mm-3D_firstorder_Kurtosis	3.6
3	original_shape_Elongation	3.5	original_glszm_ZoneEntropy	3.2
4	wavelet-LHL_glcml_Imc1	3.0	wavelet-HLL_glcml_Imc2	3.0
5	log-sigma-5-0-mm-3D_glszm_ZoneEntropy	1.3	log-sigma-2-0-mm-3D_glcml_Correlation	2.9
6	wavelet-LHH_glcml_MCC	1.2	gradient_glcml_Idmn	2.4
7	log-sigma-2-0-mm-3D_firstorder_10Percentile	1.0	wavelet-HHL_glcml_Correlation	2.0
8	wavelet-LHH_glszm_GrayLevelNonUniformityNormalized	0.7	log-sigma-3-0-mm-3D_glcml_Imc1	1.3
9			wavelet-LLH_glcml_MCC	0.8
10			wavelet-HLH_glcml_MCC	0.7
11			gradient_firstorder_Kurtosis	0.7
12			original_firstorder_Kurtosis	0.5

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# The maximal shadow feature importance is 0.9.

GLCM: gray level co-occurrence matrix; GLDM: gray level dependence matrix; GLRLM : gray level run length matrix; GLSZM: gray level size zone matrix; LOG: Laplace of Gaussian; NGTDM: Neighboring gray tone difference matrix.

Other abbreviation for specific features could be found in Pyradiomics documentation.

## Reference:

- [1] A. Zwanenburg, M. Vallières, M.A. Abdalah, H.J.W.L. Aerts, V. Andrearczyk, A. Apte, S. Ashrafinia, S. Bakas, R.J. Beukinga, R. Boellaard, M. Bogowicz, L. Boldrini, I. Buvat, G.J.R. Cook, C. Davatzikos, A. Depeursinge, M.-C. Desserot, N. Dinapoli, C.V. Dinh, S. Echegaray, I. El Naqa, A.Y. Fedorov, R. Gatta, R.J. Gillies, V. Goh, M. Götz, M. Guckenberger, S.M. Ha, M. Hatt, F. Isensee, P. Lambin, S. Leger, R.T.H. Leijenaar, J. Lenkiewicz, F. Lippert, A. Losnegård, K.H. Maier-Hein, O. Morin, H. Müller, S. Napel, C. Nioche, F. Orlhac, S. Pati, E.A.G. Pfaehler, A. Rahmim, A.U.K. Rao, J. Scherer, M.M. Siddique, N.M. Sijtsema, J. Socarras Fernandez, E. Spezi, R.J.H.M. Steenbakkers, S. Tanadini-Lang, D. Thorwarth, E.G.C. Troost, T. Upadhaya, V. Valentini, L.V. van Dijk, J. van Griethuysen, F.H.P. van Velden, P. Whybra, C. Richter, S. Löck, The Image Biomarker Standardization Initiative: Standardized Quantitative Radiomics for High-Throughput Image-based Phenotyping, *Radiology*. 295 (2020) 328–338. <https://doi.org/10.1148/radiol.2020191145>.
- [2] J.J.M. van Griethuysen, A. Fedorov, C. Parmar, A. Hosny, N. Aucoin, V. Narayan, R.G.H. Beets-Tan, J.-C. Fillion-Robin, S. Pieper, H.J.W.L. Aerts, Computational Radiomics System to Decode the Radiographic Phenotype, *Cancer Res.* 77 (2017) e104–e107. <https://doi.org/10.1158/0008-5472.CAN-17-0339>.

